autogluon_each_location

October 9, 2023

[1]:
```python
# config

label = 'y'
metric = 'mean_absolute_error'
time_limit = 60*10
presets = 'best_quality'

do_drop_ds = True

use_groups = False
n_groups = 8

auto_stack = True
num_stack_levels = 1
num_bag_folds = 0
if auto_stack:
    num_stack_levels = None
    num_bag_folds = None

use_tune_data = False
use_test_data = True
tune_and_test_length = 24*30*3 # 3 months from end, this changes the␣
↪evaluations for only test
holdout_frac = None
use_bag_holdout = False # Enable this if there is a large gap between score_val␣
↪and score_test in stack models.

sample_weight = 'sample_weight' #None
weight_evaluation = True #False
sample_weight_estimated = 1 # this changes evaluations for test and tune WTF,␣
↪cant find a fix

run_analysis = False
```

[2]:
```python
import pandas as pd
import numpy as np
```

```python
import warnings
warnings.filterwarnings("ignore")

def fix_datetime(X, name):
    # Convert 'date_forecast' to datetime format and replace original column␣
 ↪with 'ds'
    X['ds'] = pd.to_datetime(X['date_forecast'])
    X.drop(columns=['date_forecast'], inplace=True, errors='ignore')
    X.sort_values(by='ds', inplace=True)
    X.set_index('ds', inplace=True)

    # Drop rows where the minute part of the time is not 0
    X = X[X.index.minute == 0].copy()
    return X



def convert_to_datetime(X_train_observed, X_train_estimated, X_test, y_train):
    X_train_observed = fix_datetime(X_train_observed, "X_train_observed")
    X_train_estimated = fix_datetime(X_train_estimated, "X_train_estimated")
    X_test = fix_datetime(X_test, "X_test")

    # add sample weights, which are 1 for observed and 3 for estimated
    X_train_observed["sample_weight"] = 1
    X_train_estimated["sample_weight"] = sample_weight_estimated
    X_test["sample_weight"] = sample_weight_estimated

    X_train_observed["estimated_diff_hours"] = 0
    X_train_estimated["estimated_diff_hours"] = (X_train_estimated.index - pd.
 ↪to_datetime(X_train_estimated["date_calc"])).dt.total_seconds() / 3600
    X_test["estimated_diff_hours"] = (X_test.index - pd.
 ↪to_datetime(X_test["date_calc"])).dt.total_seconds() / 3600

    X_train_estimated["estimated_diff_hours"] =␣
 ↪X_train_estimated["estimated_diff_hours"].astype('int64')
    # the filled once will get dropped later anyways, when we drop y nans
    X_test["estimated_diff_hours"] = X_test["estimated_diff_hours"].fillna(-50).
 ↪astype('int64')


    X_train_estimated.drop(columns=['date_calc'], inplace=True)
    X_test.drop(columns=['date_calc'], inplace=True)

    y_train['ds'] = pd.to_datetime(y_train['time'])
    y_train.drop(columns=['time'], inplace=True)
```

```
    y_train.sort_values(by='ds', inplace=True)
    y_train.set_index('ds', inplace=True)

    return X_train_observed, X_train_estimated, X_test, y_train




def preprocess_data(X_train_observed, X_train_estimated, X_test, y_train, location):
    # convert to datetime
    X_train_observed, X_train_estimated, X_test, y_train = convert_to_datetime(X_train_observed, X_train_estimated, X_test, y_train)

    y_train["y"] = y_train["pv_measurement"].astype('float64')
    y_train.drop(columns=['pv_measurement'], inplace=True)
    X_train = pd.concat([X_train_observed, X_train_estimated])

    # fill missng sample_weight with 3
    #X_train["sample_weight"] = X_train["sample_weight"].fillna(0)


    # clip all y values to 0 if negative
    y_train["y"] = y_train["y"].clip(lower=0)

    X_train = pd.merge(X_train, y_train, how="inner", left_index=True, right_index=True)

    # print number of nans in sample_weight
    print(f"Number of nans in sample_weight: {X_train['sample_weight'].isna().sum()}")
    # print number of nans in y
    print(f"Number of nans in y: {X_train['y'].isna().sum()}")


    X_train["location"] = location
    X_test["location"] = location

    return X_train, X_test
# Define locations
locations = ['A', 'B', 'C']

X_trains = []
X_tests = []
# Loop through locations
for loc in locations:
    print(f"Processing location {loc}...")
```

```
    # Read target training data
    y_train = pd.read_parquet(f'{loc}/train_targets.parquet')

    # Read estimated training data and add location feature
    X_train_estimated = pd.read_parquet(f'{loc}/X_train_estimated.parquet')

    # Read observed training data and add location feature
    X_train_observed= pd.read_parquet(f'{loc}/X_train_observed.parquet')

    # Read estimated test data and add location feature
    X_test_estimated = pd.read_parquet(f'{loc}/X_test_estimated.parquet')

    # Preprocess data
    X_train, X_test = preprocess_data(X_train_observed, X_train_estimated,␣
 ↪X_test_estimated, y_train, loc)

    X_trains.append(X_train)
    X_tests.append(X_test)

# Concatenate all data and save to csv
X_train = pd.concat(X_trains)
X_test = pd.concat(X_tests)
```

```
Processing location A…
Number of nans in sample_weight: 0
Number of nans in y: 0
Processing location B…
Number of nans in sample_weight: 0
Number of nans in y: 4
Processing location C…
Number of nans in sample_weight: 0
Number of nans in y: 6059
```

1 Feature enginering

[3]:
```
import numpy as np
import pandas as pd

X_train.dropna(subset=['y'], inplace=True)

if not do_drop_ds:
    # add hour datetime feature
    X_train["hour"] = X_train.index.hour
    X_test["hour"] = X_test.index.hour

#print(X_train.head())
```

```
if use_groups:
    # fix groups for cross validation
    locations = X_train['location'].unique()  # Assuming 'location' is the name␣
↪of the column representing locations

    grouped_dfs = []  # To store data frames split by location

    # Loop through each unique location
    for loc in locations:
        loc_df = X_train[X_train['location'] == loc]

        # Sort the DataFrame for this location by the time column
        loc_df = loc_df.sort_index()

        # Calculate the size of each group for this location
        group_size = len(loc_df) // n_groups

        # Create a new 'group' column for this location
        loc_df['group'] = np.repeat(range(n_groups),␣
↪repeats=[group_size]*(n_groups-1) + [len(loc_df) - group_size*(n_groups-1)])

        # Append to list of grouped DataFrames
        grouped_dfs.append(loc_df)

    # Concatenate all the grouped DataFrames back together
    X_train = pd.concat(grouped_dfs)
    X_train.sort_index(inplace=True)
    print(X_train["group"].head())





to_drop = ["snow_drift:idx", "snow_density:kgm3"]

X_train.drop(columns=to_drop, inplace=True)
X_test.drop(columns=to_drop, inplace=True)

X_train.to_csv('X_train_raw.csv', index=True)
X_test.to_csv('X_test_raw.csv', index=True)
```

[4]:
```
from autogluon.tabular import TabularDataset, TabularPredictor
from autogluon.timeseries import TimeSeriesDataFrame
import numpy as np
train_data = TabularDataset('X_train_raw.csv')
```

```python
# set group column of train_data be increasing from 0 to 7 based on time, the␣
↪first 1/8 of the data is group 0, the second 1/8 of the data is group 1, etc.
train_data['ds'] = pd.to_datetime(train_data['ds'])
train_data = train_data.sort_values(by='ds')

# # print size of the group for each location
# for loc in locations:
#     print(f"Location {loc}:")
#     print(train_data[train_data["location"] == loc].groupby('group').size())


# get end date of train data and subtract 3 months
split_time = pd.to_datetime(train_data["ds"]).max() - pd.
↪Timedelta(hours=tune_and_test_length)
train_set = TabularDataset(train_data[train_data["ds"] < split_time])
test_set = TabularDataset(train_data[train_data["ds"] >= split_time])
if use_groups:
    test_set = test_set.drop(columns=['group'])

if do_drop_ds:
    train_set = train_set.drop(columns=['ds'])
    test_set = test_set.drop(columns=['ds'])
    train_data = train_data.drop(columns=['ds'])


def normalize_sample_weights_per_location(df):
    for loc in locations:
        loc_df = df[df["location"] == loc]
        loc_df["sample_weight"] = loc_df["sample_weight"] /␣
↪loc_df["sample_weight"].sum() * loc_df.shape[0]
        df[df["location"] == loc] = loc_df
    return df

tuning_data = None
if use_tune_data:
    train_data = train_set
    if use_test_data:
        # split test_set in half, use first half for tuning
        tuning_data, test_data = [], []
        for loc in locations:
            loc_test_set = test_set[test_set["location"] == loc]
            loc_tuning_data = loc_test_set.iloc[:len(loc_test_set)//2]
            loc_test_data = loc_test_set.iloc[len(loc_test_set)//2:]
            tuning_data.append(loc_tuning_data)
            test_data.append(loc_test_data)
        tuning_data = pd.concat(tuning_data)
        test_data = pd.concat(test_data)
```

```
        print("Shapes of tuning and test", tuning_data.shape[0], test_data.
↪shape[0], tuning_data.shape[0] + test_data.shape[0])

    else:
        tuning_data = test_set
        print("Shape of tuning", tuning_data.shape[0])

    # ensure sample weights for your tuning data sum to the number of rows in␣
↪the tuning data.
    tuning_data = normalize_sample_weights_per_location(tuning_data)


else:
    if use_test_data:
        train_data = train_set
        test_data = test_set
        print("Shape of test", test_data.shape[0])

# ensure sample weights for your training (or tuning) data sum to the number of␣
↪rows in the training (or tuning) data.
train_data = normalize_sample_weights_per_location(train_data)
if use_test_data:
    test_data = normalize_sample_weights_per_location(test_data)
```

```
Shape of test 5791
```

[5]:
```
if run_analysis:
    import autogluon.eda.auto as auto
    auto.dataset_overview(train_data=train_data, test_data=test_data,␣
↪label="y", sample=None)
```

[6]:
```
if run_analysis:
    auto.target_analysis(train_data=train_data, label="y")
```

2 Starting

[7]:
```
import os



# Get the last submission number
last_submission_number = int(max([int(filename.split('_')[1].split('.')[0]) for␣
↪filename in os.listdir('submissions') if "submission" in filename]))
print("Last submission number:", last_submission_number)
print("Now creating submission number:", last_submission_number + 1)

# Create the new filename
new_filename = f'submission_{last_submission_number + 1}'
```

```
hello = os.environ.get('HELLO')
if hello is not None:
    new_filename += f'_{hello}'

print("New filename:", new_filename)
```

```
Last submission number: 79
Now creating submission number: 80
New filename: submission_80
```

[8]:
```
predictors = [None, None, None]
```

[9]:
```
def fit_predictor_for_location(loc):
    print(f"Training model for location {loc}...")
    # sum of sample weights for this location, and number of rows, for both␣
 ↪train and tune data and test data
    print("Train data sample weight sum:", train_data[train_data["location"] ==␣
 ↪loc]["sample_weight"].sum())
    print("Train data number of rows:", train_data[train_data["location"] ==␣
 ↪loc].shape[0])
    if use_tune_data:
        print("Tune data sample weight sum:",␣
 ↪tuning_data[tuning_data["location"] == loc]["sample_weight"].sum())
        print("Tune data number of rows:", tuning_data[tuning_data["location"]␣
 ↪== loc].shape[0])
    if use_test_data:
        print("Test data sample weight sum:", test_data[test_data["location"]␣
 ↪== loc]["sample_weight"].sum())
        print("Test data number of rows:", test_data[test_data["location"] ==␣
 ↪loc].shape[0])
    predictor = TabularPredictor(
        label=label,
        eval_metric=metric,
        path=f"AutogluonModels/{new_filename}_{loc}",
        sample_weight=sample_weight,
        weight_evaluation=weight_evaluation,
        groups="group" if use_groups else None,
    ).fit(
        train_data=train_data[train_data["location"] == loc],
        time_limit=time_limit,
        #presets=presets,
        num_stack_levels=num_stack_levels,
        num_bag_folds=num_bag_folds if not use_groups else 2,# just put␣
 ↪somethin, will be overwritten anyways
        tuning_data=tuning_data[tuning_data["location"] == loc] if␣
 ↪use_tune_data else None,
```

```
        use_bag_holdout=use_bag_holdout,
        holdout_frac=holdout_frac,
    )

    # evaluate on test data
    if use_test_data:
        # drop sample_weight column
        t = test_data[test_data["location"] == loc]#.
↪drop(columns=["sample_weight"])
        perf = predictor.evaluate(t)
        print("Evaluation on test data:")
        print(perf[predictor.eval_metric.name])

    return predictor

loc = "A"
predictors[0] = fit_predictor_for_location(loc)
```

```
Values in column 'sample_weight' used as sample weights instead of predictive
features. Evaluation will report weighted metrics, so ensure same column exists
in test data.
Beginning AutoGluon training … Time limit = 600s
AutoGluon will save models to "AutogluonModels/submission_80_A/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.191-1 (2023-08-16)
Disk Space Avail:   311.54 GB / 315.93 GB (98.6%)
Train Data Rows:    31900
Train Data Columns: 46
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).

Training model for location A…
Train data sample weight sum: 31900
Train data number of rows: 31900
Test data sample weight sum: 2161
Test data number of rows: 2161

        Label info (max, min, mean, stddev): (5733.42, 0.0, 633.132, 1165.64686)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    132448.77 MB
```

```
        Train Data (Original)  Memory Usage: 13.08 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 3 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 42 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  1 | ['estimated_diff_hours']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 39 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])       :  1 | ['estimated_diff_hours']
                ('int', ['bool']) :  3 | ['is_day:idx', 'is_in_shadow:idx',
'wind_speed_w_1000hPa:ms']
        0.2s = Fit runtime
        43 features in original data used to generate 43 features in processed
data.
        Train Data (Processed) Memory Usage: 10.3 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.19s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
Automatically generating train/validation split with
holdout_frac=0.07836990595611286, Train Rows: 29400, Val Rows: 2500
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
```

```
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Fitting 11 L1 models …
Fitting model: KNeighborsUnif … Training model for up to 599.81s of the 599.8s
of remaining time.
        -285.3795        = Validation score   (-mean_absolute_error)
        0.04s    = Training   runtime
        0.07s    = Validation runtime
Fitting model: KNeighborsDist … Training model for up to 599.69s of the
599.68s of remaining time.
        -288.0059        = Validation score   (-mean_absolute_error)
        0.04s    = Training   runtime
        0.04s    = Validation runtime
Fitting model: LightGBMXT … Training model for up to 599.6s of the 599.6s of
remaining time.

[1000]  valid_set's l1: 178.37
[2000]  valid_set's l1: 174.975
[3000]  valid_set's l1: 173.514
[4000]  valid_set's l1: 172.456
[5000]  valid_set's l1: 172.017
[6000]  valid_set's l1: 171.584
[7000]  valid_set's l1: 171.168
[8000]  valid_set's l1: 170.818
[9000]  valid_set's l1: 170.597
[10000] valid_set's l1: 170.345

        -170.3454        = Validation score   (-mean_absolute_error)
        13.42s   = Training   runtime
        0.16s    = Validation runtime
Fitting model: LightGBM … Training model for up to 585.75s of the 585.74s of
remaining time.
```

```
[1000]  valid_set's l1: 182.44
[2000]  valid_set's l1: 180.615
[3000]  valid_set's l1: 180.212
        -180.107         = Validation score   (-mean_absolute_error)
        4.7s     = Training   runtime
        0.04s    = Validation runtime
Fitting model: RandomForestMSE … Training model for up to 580.94s of the
580.94s of remaining time.
        -187.2246        = Validation score   (-mean_absolute_error)
        7.49s    = Training   runtime
        0.1s     = Validation runtime
Fitting model: CatBoost … Training model for up to 572.87s of the 572.87s of
remaining time.
        -181.3073        = Validation score   (-mean_absolute_error)
        111.24s  = Training   runtime
        0.01s    = Validation runtime
Fitting model: ExtraTreesMSE … Training model for up to 461.59s of the 461.58s
of remaining time.
        -186.6021        = Validation score   (-mean_absolute_error)
        1.65s    = Training   runtime
        0.1s     = Validation runtime
Fitting model: NeuralNetFastAI … Training model for up to 459.35s of the
459.35s of remaining time.
        -192.4111        = Validation score   (-mean_absolute_error)
        27.11s   = Training   runtime
        0.04s    = Validation runtime
Fitting model: XGBoost … Training model for up to 432.16s of the 432.16s of
remaining time.
        -186.0713        = Validation score   (-mean_absolute_error)
        2.37s    = Training   runtime
        0.01s    = Validation runtime
Fitting model: NeuralNetTorch … Training model for up to 429.76s of the
429.75s of remaining time.
        -176.1157        = Validation score   (-mean_absolute_error)
        51.95s   = Training   runtime
        0.04s    = Validation runtime
Fitting model: LightGBMLarge … Training model for up to 377.76s of the 377.76s
of remaining time.
[1000]  valid_set's l1: 172.273
[2000]  valid_set's l1: 170.86
[3000]  valid_set's l1: 170.486
[4000]  valid_set's l1: 170.39
[5000]  valid_set's l1: 170.319
[6000]  valid_set's l1: 170.298
[7000]  valid_set's l1: 170.29
[8000]  valid_set's l1: 170.284
[9000]  valid_set's l1: 170.282
```

```
[10000] valid_set's l1: 170.28
        -170.2803        = Validation score   (-mean_absolute_error)
        43.61s   = Training   runtime
        0.27s    = Validation runtime
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
332.71s of remaining time.
        -163.223         = Validation score   (-mean_absolute_error)
        0.45s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 267.78s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_80_A/")
WARNING: eval_metric='pearsonr' does not support sample weights so they will be
ignored in reported metric.
Evaluation: mean_absolute_error on test data: -187.8065158485432
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -187.8065158485432,
    "root_mean_squared_error": -414.32909739992886,
    "mean_squared_error": -171668.60095223974,
    "r2": 0.8754434810346822,
    "pearsonr": 0.9358470155799331,
    "median_absolute_error": -12.917183456420899
}

Evaluation on test data:
-187.8065158485432
```

[10]:
```python
loc = "B"
predictors[1] = fit_predictor_for_location(loc)
```

```
Values in column 'sample_weight' used as sample weights instead of predictive
features. Evaluation will report weighted metrics, so ensure same column exists
in test data.
Beginning AutoGluon training … Time limit = 600s
AutoGluon will save models to "AutogluonModels/submission_80_B/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.191-1 (2023-08-16)
Disk Space Avail:   310.58 GB / 315.93 GB (98.3%)
Train Data Rows:    30768
Train Data Columns: 46
Label Column: y
```

```
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (1152.3, -0.0, 97.74541, 195.0957)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    130675.17 MB
        Train Data (Original)  Memory Usage: 12.62 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 3 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…

Training model for location B…
Train data sample weight sum: 30768
Train data number of rows: 30768
Test data sample weight sum: 2051
Test data number of rows: 2051

        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 42 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  1 | ['estimated_diff_hours']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 39 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])       :  1 | ['estimated_diff_hours']
                ('int', ['bool']) :  3 | ['is_day:idx', 'is_in_shadow:idx',
```

```
'wind_speed_w_1000hPa:ms']
        0.2s = Fit runtime
        43 features in original data used to generate 43 features in processed
data.
        Train Data (Processed) Memory Usage: 9.94 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.18s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
Automatically generating train/validation split with
holdout_frac=0.0812532501300052, Train Rows: 28268, Val Rows: 2500
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Fitting 11 L1 models …
Fitting model: KNeighborsUnif … Training model for up to 599.82s of the
599.81s of remaining time.
        -57.0973         = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
        0.04s    = Validation runtime
Fitting model: KNeighborsDist … Training model for up to 599.73s of the
599.73s of remaining time.
        -56.8969         = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
        0.04s    = Validation runtime
Fitting model: LightGBMXT … Training model for up to 599.65s of the 599.65s of
remaining time.
```

```
[1000]  valid_set's l1: 35.5751
[2000]  valid_set's l1: 33.3902
[3000]  valid_set's l1: 32.2742
[4000]  valid_set's l1: 31.5407
[5000]  valid_set's l1: 31.0096
[6000]  valid_set's l1: 30.6243
[7000]  valid_set's l1: 30.3162
[8000]  valid_set's l1: 30.0585
[9000]  valid_set's l1: 29.8764
[10000] valid_set's l1: 29.726

        -29.7259         = Validation score   (-mean_absolute_error)
        13.01s   = Training   runtime
        0.17s    = Validation runtime
Fitting model: LightGBM … Training model for up to 586.23s of the 586.22s of
remaining time.

[1000]  valid_set's l1: 33.0342
[2000]  valid_set's l1: 31.7436
[3000]  valid_set's l1: 31.1409
[4000]  valid_set's l1: 30.8249
[5000]  valid_set's l1: 30.6002
[6000]  valid_set's l1: 30.4238
[7000]  valid_set's l1: 30.3416
[8000]  valid_set's l1: 30.2763
[9000]  valid_set's l1: 30.2196
[10000] valid_set's l1: 30.185

        -30.185  = Validation score   (-mean_absolute_error)
        15.69s   = Training   runtime
        0.16s    = Validation runtime
Fitting model: RandomForestMSE … Training model for up to 570.13s of the
570.13s of remaining time.
        -35.3114         = Validation score   (-mean_absolute_error)
        8.75s    = Training   runtime
        0.09s    = Validation runtime
Fitting model: CatBoost … Training model for up to 560.95s of the 560.95s of
remaining time.
        -32.7391         = Validation score   (-mean_absolute_error)
        113.3s   = Training   runtime
        0.01s    = Validation runtime
Fitting model: ExtraTreesMSE … Training model for up to 447.61s of the 447.6s
of remaining time.
        -36.4349         = Validation score   (-mean_absolute_error)
        1.81s    = Training   runtime
        0.09s    = Validation runtime
Fitting model: NeuralNetFastAI … Training model for up to 445.3s of the
445.29s of remaining time.
        -40.4352         = Validation score   (-mean_absolute_error)
```

```
        25.68s   = Training   runtime
        0.03s    = Validation runtime
Fitting model: XGBoost … Training model for up to 419.55s of the 419.55s of
remaining time.
        -33.3765         = Validation score   (-mean_absolute_error)
        24.41s   = Training   runtime
        0.21s    = Validation runtime
Fitting model: NeuralNetTorch … Training model for up to 394.78s of the
394.77s of remaining time.
        -34.0567         = Validation score   (-mean_absolute_error)
        98.84s   = Training   runtime
        0.04s    = Validation runtime
Fitting model: LightGBMLarge … Training model for up to 295.89s of the 295.89s
of remaining time.

[1000]  valid_set's l1: 30.2342
[2000]  valid_set's l1: 29.3138
[3000]  valid_set's l1: 29.0572
[4000]  valid_set's l1: 28.983
[5000]  valid_set's l1: 28.955
[6000]  valid_set's l1: 28.9422
[7000]  valid_set's l1: 28.9365
[8000]  valid_set's l1: 28.9338
[9000]  valid_set's l1: 28.9325
[10000] valid_set's l1: 28.9318

        -28.9318         = Validation score   (-mean_absolute_error)
        44.72s   = Training   runtime
        0.29s    = Validation runtime
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
249.46s of remaining time.
        -28.419  = Validation score   (-mean_absolute_error)
        0.44s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 351.02s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_80_B/")
WARNING: eval_metric='pearsonr' does not support sample weights so they will be
ignored in reported metric.
Evaluation: mean_absolute_error on test data: -37.12180427631004
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -37.12180427631004,
    "root_mean_squared_error": -81.58609851989235,
    "mean_squared_error": -6656.291471697579,
    "r2": 0.7859139269118017,
```

```
    "pearsonr": 0.9104600209448434,
    "median_absolute_error": -8.015130996704102
}

Evaluation on test data:
-37.12180427631004
```

[11]:
```python
loc = "C"
predictors[2] = fit_predictor_for_location(loc)
```

```
Values in column 'sample_weight' used as sample weights instead of predictive
features. Evaluation will report weighted metrics, so ensure same column exists
in test data.
Beginning AutoGluon training … Time limit = 600s
AutoGluon will save models to "AutogluonModels/submission_80_C/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.191-1 (2023-08-16)
Disk Space Avail:   309.67 GB / 315.93 GB (98.0%)
Train Data Rows:    24492
Train Data Columns: 46
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and label-values can't be converted to int).
        Label info (max, min, mean, stddev): (999.6, 0.0, 78.11911, 167.50151)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    130353.95 MB
        Train Data (Original)  Memory Usage: 10.04 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 2 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
```

```
        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 42 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  1 | ['estimated_diff_hours']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 40 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])       :  1 | ['estimated_diff_hours']

Training model for location C…
Train data sample weight sum: 24492
Train data number of rows: 24492
Test data sample weight sum: 1579
Test data number of rows: 1579

                ('int', ['bool']) :  2 | ['is_day:idx', 'is_in_shadow:idx']
        0.1s = Fit runtime
        43 features in original data used to generate 43 features in processed
data.
        Train Data (Processed) Memory Usage: 8.08 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.16s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
Automatically generating train/validation split with holdout_frac=0.1, Train
Rows: 22042, Val Rows: 2450
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
```

```
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Fitting 11 L1 models …
Fitting model: KNeighborsUnif … Training model for up to 599.84s of the
599.83s of remaining time.
        -33.2822         = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
        0.05s    = Validation runtime
Fitting model: KNeighborsDist … Training model for up to 599.74s of the
599.74s of remaining time.
        -33.3446         = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
        0.1s     = Validation runtime
Fitting model: LightGBMXT … Training model for up to 599.6s of the 599.59s of
remaining time.

[1000]  valid_set's l1: 18.9213
[2000]  valid_set's l1: 18.3545
[3000]  valid_set's l1: 18.1711
[4000]  valid_set's l1: 18.08
[5000]  valid_set's l1: 18.0196
[6000]  valid_set's l1: 17.9721
[7000]  valid_set's l1: 17.9335
[8000]  valid_set's l1: 17.9153
[9000]  valid_set's l1: 17.9061
[10000] valid_set's l1: 17.8961

        -17.8909         = Validation score   (-mean_absolute_error)
        12.9s    = Training   runtime
        0.18s    = Validation runtime
Fitting model: LightGBM … Training model for up to 586.2s of the 586.2s of
remaining time.

[1000]  valid_set's l1: 19.115
[2000]  valid_set's l1: 18.8635
[3000]  valid_set's l1: 18.8186
[4000]  valid_set's l1: 18.7676
[5000]  valid_set's l1: 18.7493
[6000]  valid_set's l1: 18.7353
[7000]  valid_set's l1: 18.7294
[8000]  valid_set's l1: 18.7245
[9000]  valid_set's l1: 18.7201
[10000] valid_set's l1: 18.7209
```

```
	-18.7199	 = Validation score   (-mean_absolute_error)
	13.65s	 = Training   runtime
	0.16s	 = Validation runtime
Fitting model: RandomForestMSE … Training model for up to 572.1s of the
572.09s of remaining time.
	-20.2022	 = Validation score   (-mean_absolute_error)
	4.85s	 = Training   runtime
	0.1s	 = Validation runtime
Fitting model: CatBoost … Training model for up to 566.99s of the 566.98s of
remaining time.
	-18.5962	 = Validation score   (-mean_absolute_error)
	117.36s	 = Training   runtime
	0.01s	 = Validation runtime
Fitting model: ExtraTreesMSE … Training model for up to 449.59s of the 449.58s
of remaining time.
	-20.1925	 = Validation score   (-mean_absolute_error)
	1.09s	 = Training   runtime
	0.09s	 = Validation runtime
Fitting model: NeuralNetFastAI … Training model for up to 448.24s of the
448.23s of remaining time.
	-20.3136	 = Validation score   (-mean_absolute_error)
	20.56s	 = Training   runtime
	0.04s	 = Validation runtime
Fitting model: XGBoost … Training model for up to 427.6s of the 427.6s of
remaining time.
	-18.7778	 = Validation score   (-mean_absolute_error)
	23.62s	 = Training   runtime
	0.21s	 = Validation runtime
Fitting model: NeuralNetTorch … Training model for up to 403.62s of the
403.61s of remaining time.
	-18.985	 = Validation score   (-mean_absolute_error)
	79.03s	 = Training   runtime
	0.04s	 = Validation runtime
Fitting model: LightGBMLarge … Training model for up to 324.54s of the 324.54s
of remaining time.

[1000]	valid_set's l1: 18.3614
[2000]	valid_set's l1: 18.2652
[3000]	valid_set's l1: 18.2436
[4000]	valid_set's l1: 18.238
[5000]	valid_set's l1: 18.2362
[6000]	valid_set's l1: 18.2354
[7000]	valid_set's l1: 18.2351
[8000]	valid_set's l1: 18.235
[9000]	valid_set's l1: 18.235
[10000]	valid_set's l1: 18.235

	-18.235	 = Validation score   (-mean_absolute_error)
	41.84s	 = Training   runtime
```

```
        0.33s    = Validation runtime
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
281.19s of remaining time.
        -17.067  = Validation score   (-mean_absolute_error)
        0.44s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 319.27s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_80_C/")
WARNING: eval_metric='pearsonr' does not support sample weights so they will be
ignored in reported metric.
Evaluation: mean_absolute_error on test data: -30.572163854274063
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -30.572163854274063,
    "root_mean_squared_error": -63.30322207779981,
    "mean_squared_error": -4007.297925431241,
    "r2": 0.7898966511946184,
    "pearsonr": 0.8943101764263846,
    "median_absolute_error": -3.0131614208221436
}

Evaluation on test data:
-30.572163854274063
```

3 Submit

[12]:
```python
import pandas as pd
import matplotlib.pyplot as plt

train_data_with_dates = TabularDataset('X_train_raw.csv')
train_data_with_dates["ds"] = pd.to_datetime(train_data_with_dates["ds"])

test_data = TabularDataset('X_test_raw.csv')
test_data["ds"] = pd.to_datetime(test_data["ds"])
#test_data
```

```
Loaded data from: X_train_raw.csv | Columns = 48 / 48 | Rows = 92951 -> 92951
Loaded data from: X_test_raw.csv | Columns = 47 / 47 | Rows = 2160 -> 2160
```

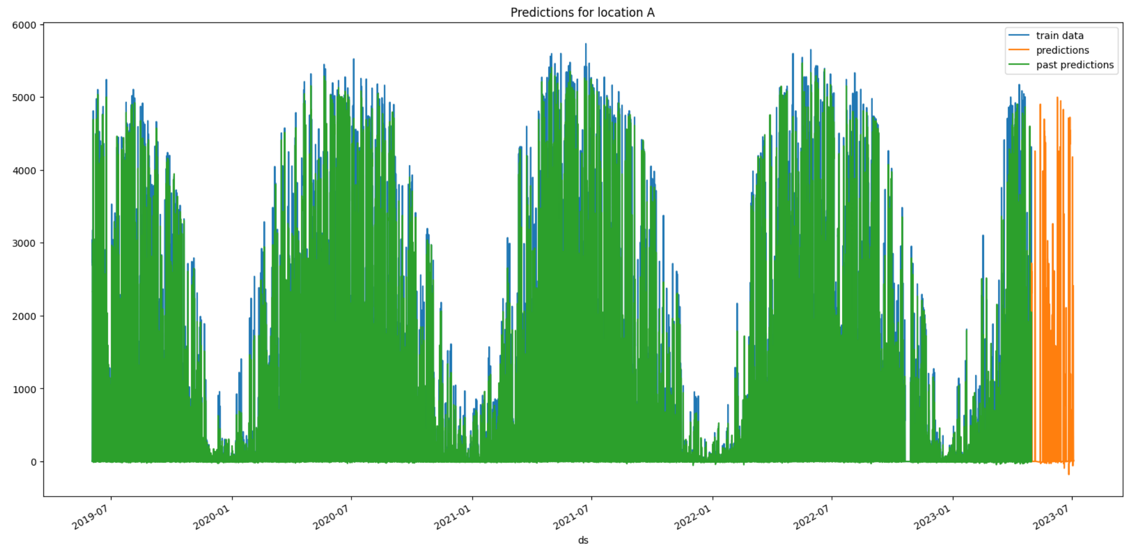
[13]:
```python
test_ids = TabularDataset('test.csv')
test_ids["time"] = pd.to_datetime(test_ids["time"])
# merge test_data with test_ids
test_data_merged = pd.merge(test_data, test_ids, how="inner", right_on=["time",␣
 ↪"location"], left_on=["ds", "location"])
```

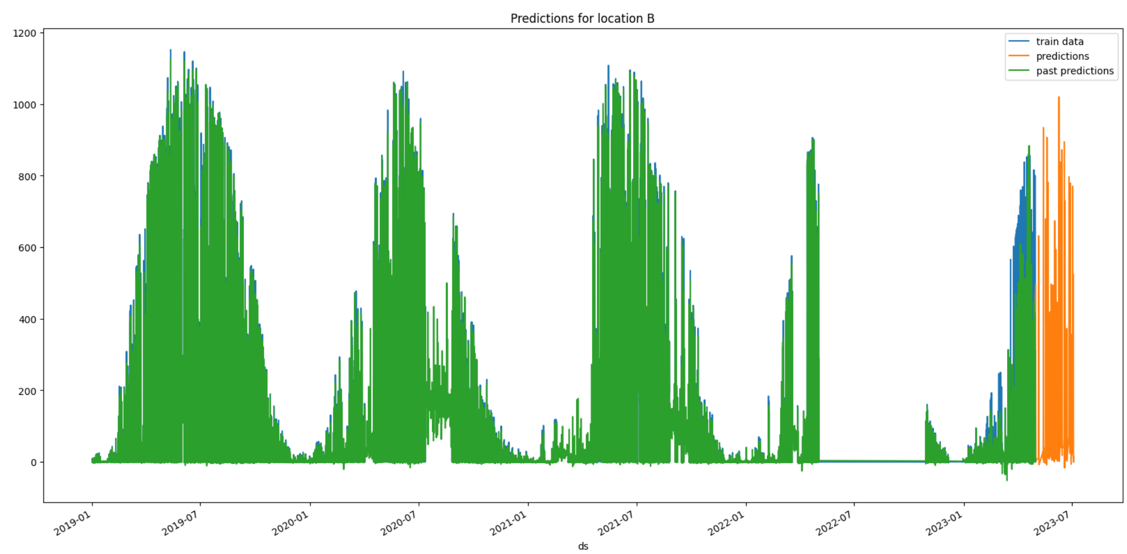
```
#test_data_merged
```

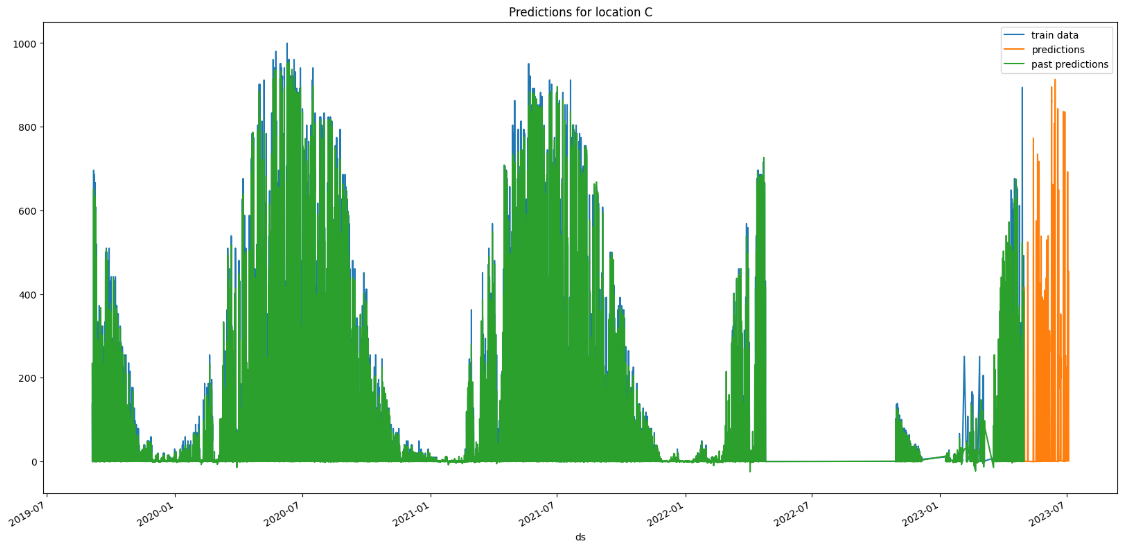
Loaded data from: test.csv | Columns = 4 / 4 | Rows = 2160 -> 2160

[14]:
```
# predict, grouped by location
predictions = []
location_map = {
    "A": 0,
    "B": 1,
    "C": 2
}
for loc, group in test_data.groupby('location'):
    i = location_map[loc]
    subset = test_data_merged[test_data_merged["location"] == loc].
 ↪reset_index(drop=True)
    #print(subset)
    pred = predictors[i].predict(subset)
    subset["prediction"] = pred
    predictions.append(subset)

    # get past predictions
    past_pred = predictors[i].
 ↪predict(train_data_with_dates[train_data_with_dates["location"] == loc])
    train_data_with_dates.loc[train_data_with_dates["location"] == loc,␣
 ↪"prediction"] = past_pred
```

[15]:
```
# plot predictions for location A, in addition to train data for A
for loc, idx in location_map.items():
    fig, ax = plt.subplots(figsize=(20, 10))
    # plot train data
    train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
 ↪y='y', ax=ax, label="train data")

    # plot predictions
    predictions[idx].plot(x='ds', y='prediction', ax=ax, label="predictions")

    # plot past predictions
    train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
 ↪y='prediction', ax=ax, label="past predictions")

    # title
    ax.set_title(f"Predictions for location {loc}")
```


Predictions for location A
train data
predictions
past predictions
6000
5000
4000
3000
2000
1000
0
2019-07
2020-01
2020-07
2021-01
2021-07
2022-01
2022-07
2023-01
2023-07
ds


Predictions for location B
train data
predictions
past predictions
1200
1000
800
600
400
200
0
2019-01
2019-07
2020-01
2020-07
2021-01
2021-07
2022-01
2022-07
2023-01
2023-07
ds



[16]:
```python
# concatenate predictions
submissions_df = pd.concat(predictions)
submissions_df = submissions_df[["id", "prediction"]]
submissions_df
```

[16]:
```
       id  prediction
0       0   -2.451493
1       1   -2.136074
2       2   -0.487430
3       3   44.617561
4       4  357.281982
..    …         …
715  2155   57.938728
716  2156   36.972794
717  2157   10.466211
718  2158    1.646137
719  2159    1.249219

[2160 rows x 2 columns]
```

[17]:
```python
# Save the submission DataFrame to submissions folder, create new name based on
 ↪last submission, format is submission_<last_submission_number + 1>.csv

# Save the submission
print(f"Saving submission to submissions/{new_filename}.csv")
submissions_df.to_csv(os.path.join('submissions', f"{new_filename}.csv"),
 ↪index=False)
print("jall1a")
```

```
Saving submission to submissions/submission_80.csv
jall1a
```

[18]:
```python
# save this running notebook
from IPython.display import display, Javascript
import time

# hei123

display(Javascript("IPython.notebook.save_checkpoint();"))

time.sleep(3)
```

```
&lt;IPython.core.display.Javascript object&gt;
```

[19]:
```python
# save this notebook to submissions folder
import subprocess
import os
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
 ↪join('notebook_pdfs', f"{new_filename}.pdf"), "autogluon_each_location.
 ↪ipynb"])
```

```
[NbConvertApp] Converting notebook autogluon_each_location.ipynb to pdf
/opt/conda/lib/python3.10/site-packages/nbconvert/utils/pandoc.py:51:
RuntimeWarning: You are using an unsupported version of pandoc (2.9.2.1).
Your version must be at least (2.14.2) but less than (4.0.0).
Refer to https://pandoc.org/installing.html.
Continuing with doubts…
  check_pandoc_version()
[NbConvertApp] Writing 107933 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 88364 bytes to notebook_pdfs/submission_80.pdf
```

[19]:
```
CompletedProcess(args=['jupyter', 'nbconvert', '--to', 'pdf', '--output',
'notebook_pdfs/submission_80.pdf', 'autogluon_each_location.ipynb'],
returncode=0)
```

[20]:
```python
# feature importance
location="A"
split_time = pd.Timestamp("2022-10-28 22:00:00")
estimated = train_data_with_dates[train_data_with_dates["ds"] >= split_time]
estimated = estimated[estimated["location"] == location]
predictors[0].feature_importance(feature_stage="original", data=estimated,␣
 ↪time_limit=60*10)
```

```
These features in provided data are not utilized by the predictor and will be
ignored: ['ds', 'elevation:m', 'sample_weight', 'location', 'prediction']
Computing feature importance via permutation shuffling for 43 features using
4394 rows with 10 shuffle sets… Time limit: 600s…
        527.31s = Expected runtime (52.73s per shuffle set)
        296.08s = Actual runtime (Completed 10 of 10 shuffle sets)
```

[20]:

```
                              importance    stddev       p_value   n  \
direct_rad:W                  147.111766  2.176199  2.728679e-18  10
clear_sky_rad:W                88.789385  1.940390  9.137558e-17  10
diffuse_rad:W                  78.019292  2.133635  6.869250e-16  10
sun_azimuth:d                  56.670397  3.018095  2.746007e-13  10
sun_elevation:d                33.984099  0.972222  1.030239e-15  10
direct_rad_1h:J                28.152551  0.600915  7.392124e-17  10
clear_sky_energy_1h:J          27.416397  1.190033  4.372890e-14  10
diffuse_rad_1h:J               15.161300  0.741926  1.284197e-13  10
total_cloud_cover:p            14.086562  0.636443  6.268595e-14  10
effective_cloud_cover:p        12.502470  0.835651  2.108495e-12  10
wind_speed_u_10m:ms             9.767501  1.054446  1.536273e-10  10
cloud_base_agl:m                7.589931  0.452026  7.490421e-13  10
is_day:idx                      6.359774  0.328628  2.093811e-13  10
visibility:m                    5.828035  0.524073  3.004598e-11  10
snow_water:kgm2                 5.682946  0.834743  2.368539e-09  10
relative_humidity_1000hPa:p     5.646109  0.588591  1.124939e-10  10
ceiling_height_agl:m            5.453995  0.415181  6.765601e-12  10
fresh_snow_24h:cm               5.347722  0.684959  7.034902e-10  10
msl_pressure:hPa                5.049854  0.569148  2.255062e-10  10
wind_speed_10m:ms               4.526295  0.654019  2.048277e-09  10
is_in_shadow:idx                4.427495  0.273039  1.024165e-12  10
pressure_50m:hPa                4.083450  0.569790  1.503712e-09  10
wind_speed_v_10m:ms             4.031230  0.700483  1.041920e-08  10
sfc_pressure:hPa                3.598798  0.589320  6.183099e-09  10
pressure_100m:hPa               3.595549  0.573325  4.890576e-09  10
t_1000hPa:K                     2.035832  1.175175  1.955336e-04  10
estimated_diff_hours            1.725568  0.172421  7.706771e-11  10
fresh_snow_6h:cm                1.596119  0.229132  1.933599e-09  10
fresh_snow_12h:cm               1.518177  0.306898  3.914704e-08  10
air_density_2m:kgm3             1.361581  0.550849  1.331568e-05  10
super_cooled_liquid_water:kgm2  1.205138  0.336866  6.350857e-07  10
snow_depth:cm                   1.185776  0.372307  1.685825e-06  10
precip_5min:mm                  0.986953  0.423080  2.102601e-05  10
fresh_snow_3h:cm                0.847326  0.204491  1.814081e-07  10
dew_point_2m:K                  0.682033  0.427291  3.463186e-04  10
precip_type_5min:idx            0.587061  0.292100  6.600589e-05  10
dew_or_rime:idx                 0.516153  0.187415  5.580908e-06  10
fresh_snow_1h:cm                0.400973  0.194604  5.471623e-05  10
rain_water:kgm2                 0.162171  0.113489  7.247112e-04  10
```

prob_rime:p	0.045152	0.143556	1.729571e-01	10
wind_speed_w_1000hPa:ms	0.000000	0.000000	5.000000e-01	10
snow_melt_10min:mm	-0.104706	0.110621	9.924385e-01	10
absolute_humidity_2m:gm3	-0.262476	0.207911	9.984264e-01	10

	p99_high	p99_low
direct_rad:W	149.348220	144.875311
clear_sky_rad:W	90.783502	86.795269
diffuse_rad:W	80.212004	75.826580
sun_azimuth:d	59.772058	53.568736
sun_elevation:d	34.983240	32.984958
direct_rad_1h:J	28.770104	27.534998
clear_sky_energy_1h:J	28.639380	26.193414
diffuse_rad_1h:J	15.923768	14.398832
total_cloud_cover:p	14.740626	13.432497
effective_cloud_cover:p	13.361259	11.643682
wind_speed_u_10m:ms	10.851142	8.683859
cloud_base_agl:m	8.054472	7.125389
is_day:idx	6.697500	6.022047
visibility:m	6.366619	5.289451
snow_water:kgm2	6.540801	4.825090
relative_humidity_1000hPa:p	6.250998	5.041221
ceiling_height_agl:m	5.880672	5.027318
fresh_snow_24h:cm	6.051646	4.643798
msl_pressure:hPa	5.634761	4.464948
wind_speed_10m:ms	5.198422	3.854168
is_in_shadow:idx	4.708094	4.146896
pressure_50m:hPa	4.669017	3.497883
wind_speed_v_10m:ms	4.751108	3.311352
sfc_pressure:hPa	4.204435	2.993161
pressure_100m:hPa	4.184749	3.006349
t_1000hPa:K	3.243546	0.828118
estimated_diff_hours	1.902763	1.548373
fresh_snow_6h:cm	1.831595	1.360643
fresh_snow_12h:cm	1.833572	1.202782
air_density_2m:kgm3	1.927683	0.795480
super_cooled_liquid_water:kgm2	1.551332	0.858945
snow_depth:cm	1.568392	0.803160
precip_5min:mm	1.421747	0.552159
fresh_snow_3h:cm	1.057479	0.637173
dew_point_2m:K	1.121155	0.242911
precip_type_5min:idx	0.887249	0.286873
dew_or_rime:idx	0.708757	0.323548
fresh_snow_1h:cm	0.600965	0.200980
rain_water:kgm2	0.278803	0.045539
prob_rime:p	0.192682	-0.102379
wind_speed_w_1000hPa:ms	0.000000	0.000000

```
snow_melt_10min:mm                0.008979   -0.218390
absolute_humidity_2m:gm3         -0.048808   -0.476143
```

[ ]:
```
# feature importance
observed = train_data_with_dates[train_data_with_dates["ds"] < split_time]
observed = observed[observed["location"] == location]
predictors[0].feature_importance(feature_stage="original", data=observed,␣
↪time_limit=60*10)
```

```
These features in provided data are not utilized by the predictor and will be
ignored: ['ds', 'elevation:m', 'sample_weight', 'location', 'prediction']
Computing feature importance via permutation shuffling for 43 features using
5000 rows with 10 shuffle sets… Time limit: 600s…
        598.8s  = Expected runtime (59.88s per shuffle set)
```

[ ]:
```
display(Javascript("IPython.notebook.save_checkpoint();"))
time.sleep(3)

subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}_with_feature_importance.pdf"),␣
↪"autogluon_each_location.ipynb"])
```

[ ]:
```
# import subprocess

# def execute_git_command(directory, command):
#     """Execute a Git command in the specified directory."""
#     try:
#         result = subprocess.check_output(['git', '-C', directory] + command,␣
↪stderr=subprocess.STDOUT)
#         return result.decode('utf-8').strip(), True
#     except subprocess.CalledProcessError as e:
#         print(f"Git command failed with message: {e.output.decode('utf-8').
↪strip()}")
#         return e.output.decode('utf-8').strip(), False

# git_repo_path = "."

# execute_git_command(git_repo_path, ['config', 'user.email',␣
↪'henrikskog01@gmail.com'])
# execute_git_command(git_repo_path, ['config', 'user.name', hello if hello is␣
↪not None else 'Henrik eller Jørgen'])

# branch_name = new_filename

# # add datetime to branch name
# branch_name += f"_{pd.Timestamp.now().strftime('%Y-%m-%d_%H-%M-%S')}"
```

```
# commit_msg = "run result"

# execute_git_command(git_repo_path, ['checkout', '-b',branch_name])

# # Navigate to your repo and commit changes
# execute_git_command(git_repo_path, ['add', '.'])
# execute_git_command(git_repo_path, ['commit', '-m',commit_msg])

# # Push to remote
# output, success = execute_git_command(git_repo_path, ['push',␣
↪'origin',branch_name])

# # If the push fails, try setting an upstream branch and push again
# if not success and 'upstream' in output:
#     print("Attempting to set upstream and push again...")
#     execute_git_command(git_repo_path, ['push', '--set-upstream',␣
↪'origin',branch_name])
#     execute_git_command(git_repo_path, ['push', 'origin', 'henrik_branch'])

# execute_git_command(git_repo_path, ['checkout', 'main'])
```